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Automated cloud motion tracking using satellite imagery and deep learning

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Abstract

CMT with clouds forms a critical aspect in the weather prediction, climatology, aircraft safety, and control of disasters. Conventional methods of cloud monitoring typically use the human interpretation and standard image-processing algorithms, which can be time-intensive and may not be as efficient to process a high number of satellite images. The research suggests a technical system of automated cloud motion tracking via satellite imagery and deep learning algorithms to enhance accuracy and efficiency in detecting, tracking, and predicting clouds. The overall methodology will involve the use of U-Net (cloud segmentation), Convolutional Neural Networks (CNNs) (spatial features), and Convolutional Long Short-Term memory (ConvLSTM) networks (temporal), robotically moving clouds. The satellite images of multiple periods undergo preprocessing steps of normalization, enhancement, noise reduction, and then proceed to be analyzed using the deep learning models. The model has high segmentation accuracy, valid cloud feature detection, and accurate forecasting of cloud movement in various atmospheric conditions as evidenced by experimental results. The combination model is very successful in both spatial and temporal features to represent clouds, and make up the proper estimation of cloud courses, and future cloud locations. Accuracy, Precision, Recall, F1-Score and root mean square error (RMSE) performance analysis proves the usefulness of the suggested method. The results show that deep learning cloud motion monitoring can greatly improve the short-term weather forecasting and surveillance functions. The suggested framework offers an intelligent systems scaling approach to large-scale satellite datasets processing and it can facilitate the development of automated meteorological systems to predict weather.

Keywords: Cloud Motion Tracking, Satellite Imagery, Deep Learning, CNN, U-Net, ConvLSTM, Remote Sensing, Weather Forecasting, Cloud Segmentation, Spatiotemporal Analysis, Artificial Intelligence, Environmental Monitoring

1. Introduction

The atmosphere of the earth is greatly impacted by clouds in various aspects as they affect the weather conditions, the ways in which it rains and the climatic conditions. Weather forecasting, disaster management, aviation safety as well as climate research require accurate tracking and monitoring of cloud movement. Conventionally, to monitor the movement of clouds and predict their future, meteorologists have used satellite images and optical flow. Nonetheless, taking out the satellite data in bulk, manually, is both time- and labor-intensive, and may not give real-time data which is essential in current forecasting systems [1]. The new developments in remote sensing technologies in satellites have led to the persistent creation of the high resolution and multi-temporal Earth observation images. These data sets are useful in terms of cloud formation, movement and development in various geographical regions. Meanwhile, advancements in the field of artificial intelligence and deep learning have opened up new possibilities in automating the process of analyzing intricate visual patterns in the satellite photos. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Convolutional Long Short-Term Memory (ConvLSTM) networks, are deep learning models that have excelled in performing image recognition, object tracking, and spatiotemporal tasks like data analysis. Satellite images and deep learning. Automated cloud motion tracking seeks to use these technological developments to precisely track, detect and forecast cloud patterns [2]. Deep learning algorithms can produce cloud motion vectors, identify developing weather systems, and enhance the accuracy of short-term predictions by learning the spatial and temporal correlation using a sequence of satellite images. Such automated solutions lessen the reliance on manual interpretation and increase the efficiency and dependability of the meteorological observations [3]. This study aims at creating a deep learning model of a cloud motion tracking system based on satellite images and automated. The research aims at investigating the advanced image processing methods and machine learning in

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cloud detection and classification and estimation of motion. The results will be aimed at leading to better weather forecasting, better climate surveillance, as well as better usage of satellite-based Earth observation data towards environmental and atmospheric needs.

2. Related Works

The majority of new developments in AI deep learning and remote sensing recently have enhanced the capacity to process huge quantities of image data to perform environmental monitoring and prediction tasks. These inventions give a solid basis of automated cloud motion tracking with the help of satellite images. Different deep learning models have been investigated by researchers in the field of object detection, picture segmentation, time forecasting, and pattern recognition in different fields proving that artificial intelligence is effective in dealing with complex visual images. Farjon *et al.* [15] have made a detailed review of the counting techniques using deep-learning in precision agriculture. Their paper emphasized that convolutional neural networks (CNNs) and object detection systems are capable of automatically detecting and counting objects in both airborne and terrestrial pictures. The results showed how deep learning is effective in extracting spatial information of complex image datasets, the use of which is directly applicable to cloud detection and feature extraction of satellite images.

A systematic review on object detection algorithms to use in optical remote sensing images was undertaken by Fontanet and Piero [16]. They tested modern deep learning frameworks, such as YOLO and Faster R-CNN, and transformer frameworks to detect objects in high-resolution satellite imagery. The paper has highlighted the need to have correct feature localization and detection as a key element of cloud tracking systems. Galvez-Salido *et al.* [17] used the methods of deep learning and computer vision to analyze biological images and do quantitative follow-ups. Their study showed that deep neural networks are able to detect the complex structures and temporal variations in sequence of images in an accurate manner. The article pointed to the possibility of artificial intelligence to be used in automated monitoring applications, which can be applied to monitor moving clouds.

Ghali and Akhloufi [18] created a deep-learning-based system of wildland fire recognition based on RGB and thermal infrared aerial imagery. Their findings indicated that the ability of image modalities to be used across several modalities, greatly enhanced the accuracy of detection. This method offers useful information to the cloud motion tracking which may incorporate visible channel and infrared channel satellites to suitably improve cloud sensing and predicting abilities. Hammad *et al.* [19] were able to overview precision farming implementation that uses unmanned aerial vehicles (UAVs) and smart monitoring systems. They found automated image analysis and real-time decision support systems to be critical and need to be implemented in operational cloud monitors and weather forecast systems too.

Huihui *et al.* [20] found out the applications of deep learning in smart soybean farming and wrote about the challenges with image processing, prediction accuracy and model generalization. Their paper emphasized both the usefulness of a convolutional and recurrent neural network in temporally analyzing image data, and this is greatly applicable to cloud movement prediction. The researchers, Junlin *et al.* [21], have conducted a review of the deep learning methods in the prediction of sea ice. Their studies established the benefits of

recurrent neural networks and ConvLSTM networks in the use of models of spatiotemporal environmental processes using the models. The experiment proved that deep learning is an effective model to represent time dynamics, and that ConvLSTM would be a good alternative to forecast cloud movements.

Kangyu *et al.* [22] suggested UAV LiDAR and RGB observations as a method to estimate the forest aboveground biomass. Their study showed that deep learning models can be used to derive important attributes of the environment in terms of a remotely sensed signal, which supports the feasibility of these methods towards the atmospheric control procedure. Kashif *et al.* [23] considered artificial intelligence applications in maritime security and talked about the machine learning technique used to predict, monitor and perform surveillance. They found an accelerating contribution of AI to the processing and production of massive spatial data and actionable predictions based on dynamic environmental processes. Khan *et al.* [24] conducted a review of automated methods to detect plant diseases and stressed the significance of image segmentation, extraction of features by deep learning, and the classification of these features. The research indicated that the high-level neural networks are capable of high detection in the visually complicated conditions which justifies their application in cloud segmentation and classification.

Chandel and Leonard [25] were able to suggest an end-to-end digital diagnosis and management of precise crop diseases via sensing technologies and artificial intelligence. Their work emphasized the combination of the data collection, image analysis and predictive modelling that is highly similar to the working process needed in automated cloud motion tracking systems. Li *et al.* [26] based their research on the use of artificial intelligence and deep learning in the remote sensing of the Arctic sea ice. Their experiment showed that satellite images that are analyzed using deep learning models can enhance environmental monitoring and prediction. Important information on cloud motion prediction that uses satellite data was also made available by the authors to find vulnerabilities in applying the spatiotemporal learning methods to improve the precision of forecasts.

On the whole, the literature reviewed helps to conclude that the methods of deep learning have become a tremendous success in image analysis, object detection, environmental monitoring, and forecasts in time. Nonetheless, few research works have given special attention to automated Cloud motion tracking with a combination of CNN, U-Net and ConvLSTM models. Hence, this study attempts to overcome this gap by coming up with an all-inclusive deep learning architecture, which can precisely identify, trace and predict cloud patterns based on satellite images to enhance the use of weather forecasts in weather prediction.

3. Methods and Materials

3.1 Research Methodology

The current paper suggests a satellite-based, deep learning, and automated cloud motion tracking system. The methodology incorporates the use of satellite images in the acquisition, preprocessing, cloud segmentation, extraction of features, estimating of cloud movement and predictive analysis. Multi-temporal satellite images refer to the meteorological satellite platforms, which are used to capture multi-temporal satellite images and process them to understand the structure of the clouds and their motion patterns with time [4]. Side by side cloud sequences of images have spatial and temporal features which

are learnt with deep learning models. The general workflow includes data collection, image processing, model training, cloud tracking, as well as the performance evaluation.

The suggested framework should enhance the accuracy of estimating the cloud movements and minimize the usage of manual operation. Figure-independent processing can be used to continuously monitor the conditions of the atmosphere and provides application to short-term weather forecasting [5].

3.2 Materials and Dataset

The main source of data in this research is taken using satellite imagery. Geostationary and polar bear satellites provide multi-temporal cloud images to give an ongoing impression of the atmosphere. The pictures contain the visible, infrared, and water vapor channels, which have vital data concerning cloud formations and movement.

Table 1: Dataset Characteristics

Parameter	Description
Data Source	Meteorological Satellite Imagery
Image Type	Visible, Infrared, Water Vapor
Spatial Resolution	0.5–4 km
Temporal Resolution	10–30 minutes
Image Format	GeoTIFF, HDF5, NetCDF
Study Period	Multiple Weather Seasons
Coverage Area	Regional and Global
Target Objects	Cloud Systems and Atmospheric Features

The dataset will be segregated into training, validation and testing data sets so as to guarantee a sound model development and evaluation. Usually, 70 percent of the data is utilized in training, 15 percent in validation and 15 percent in testing.

3.3 Data Preprocessing

The noise on satellite images and the gaps of values, as well as the variations of the lighting, and the atmospheric distortions are a common thing [6]. Thus, before training models, preprocessing is carried out. The preprocessing phase consists of:

- Normalization and resizing of images.
- Filtering to reduce noise.
- Enhanced contrast to gain more visibility of the clouds.
- Time synchronization of image sequences.
- Cloud mask generation.
- Rotation, flipping, scaling of data.

Normalization brings the pixel values to a unified range which enhances model convergence in training. The augmentation augments diversity in the datasets and rigorously boosts generalization capacity in the models.

3.4 Deep Learning Algorithms

Automated cloud motion tracking is achieved through the use of three deep learning algorithms.

3.4.1 Convolutional Neural Network (CNN)

CNN is applied in cloud detection and detection of features in satellite images. Convolutional layers can automatically learn spatial features like cloud boundaries, textures and shapes. The pooling layers minimize the computing process, but maintain significant data.

The CNN model derives the features of high level clouds, which is used as the input to future tracking and prediction. The model is learnt with the help of marked up images of clouds and refined by backpropagation [7].

Advantages:

- Efficient feature extraction.
- High accuracy in image classification.
- Robust performance on large image datasets.
- Accurate pixel-level segmentation.
- Effective for small and complex cloud structures.
- Requires relatively fewer training samples.
- Captures temporal dependencies.
- Can be used in sequence prediction.
- Dynamic forecasting capability of the cloud systems.

Table 2: Comparison of Selected Algorithms

Algorithm	Primary Function	Strengths	Limitations
CNN	Feature Extraction	Fast learning, high accuracy	Limited temporal analysis
U-Net	Cloud Segmentation	Precise pixel classification	Computationally intensive
ConvLSTM	Motion Prediction	Handles spatial-temporal data	Requires large training datasets

3.4.2 U-Net Segmentation Network

U-Net is used to make fine-tuned cloud segmentation. The architecture is an encoder decoder design with skip connections that conserve the spatial information when rebuilding images. Contextual cloud information is captured by the encoder, and pixel level cloud masks are produced by the decoder. U-Net is especially the most appropriate in remote sensing applications since it will effectively distinguish the areas of clouds and the background atmospheric features.

3.4.3 ConvLSTM Network

ConvLSTM is a frames / image sequence model that is relying on both convolutional processes and Long Short-Term Memory to simulate the relationships in both time and space in sequential satellite images.

Contrary to the conventional LSTM networks, ConvLSTM does not lose spatial data during learning, and it also learns the temporal dynamics of cloud evolution. The network predicts the

positions of clouds in the future, by using the past sequences of images and creates the cloud motion vectors [8].

3.5 Proposed Framework

The suggested pipeline consists of the stages:

Step 1: Data Acquisition

The satellite cloud images are gathered through meteorological databases.

Step 2: Preprocessing

Images are normalized, enhanced and noise removed.

Step 3: Cloud Segmentation

U-Net detects cloud regions, and produces segmentation masks.

Step 4: Feature Extraction

CNN derives the spatial cloud features in segmented images.

Step 5: Motion Tracking

ConvLSTM processes the sequence of images and computes the vectors of motion of the clouds.

Step 6: Prediction

The future position of the clouds are increased and the movement trajectory determined.

Step 7: Evaluation

Quantitative measures are used to measure model performance.

3.6 Pseudocode of the Proposed Method

“**Algorithm:** Automated Cloud Motion Tracking

Input:

Satellite Image Sequence S

Output:

Cloud Motion Vectors M

Future Cloud Position P

Begin

1. Load satellite image sequence S
2. Perform image preprocessing
 - a) Resize images
 - b) Normalize pixel values
 - c) Remove noise
 - d) Enhance contrast
3. Apply U-Net segmentation
Generate cloud masks C
4. Extract cloud features using CNN

$F = \text{CNN}(C)$

5. Create temporal image sequences

$T = \text{Sequence}(F)$

6. Train ConvLSTM model

$\text{Model} \leftarrow \text{ConvLSTM}(T)$

7. Predict cloud movement

$M \leftarrow \text{Model.predict}()$

8. Estimate future cloud positions

$P \leftarrow \text{Forecast}(M)$

9. Evaluate predictions using:

- Accuracy
- Precision
- Recall
- F1-Score
- RMSE

10. Display cloud motion vectors

11. Output predicted cloud trajectory

End”

3.7 Performance Evaluation Metrics

The performance of the proposed cloud tracking system is measured with various performance measures.

Accuracy

Accuracy is used to indicate the percent of correctly-classified cloud and non-cloud pixels.

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN)$$

Precision

Accuracy is used to assess the accuracy of cloud detections.

$$\text{Precision} = TP/(TP + FP)$$

Recall

Recall the capacity to recognize real cloudy areas.

$$\text{Recall} = TP/(TP + FN)$$

F1-Score

F1-score is used to balance precision and recall to comprehensively assess data.

Root Mean Square Error (RMSE)

The RMSE is used to measure the error between projected and measured positions of the clouds in motion tracking. The smaller the RMSE, the better the forecasting.

3.8 Implementation Environment

Deep learning libraries, which use Python, are used to implement the proposed framework. TensorFlow and PyTorch frameworks are used to do model development and training. Resource-on-rapid Instruction (ROR): The training and inference are speeded up using high-performance computing resources with Graphics Processing Unit (GPUs) ^[9].

Experimental environment consists of:

- **Programming Language:** Python
- **Deep Learning Frameworks:** TensorFlow, PyTorch
- **Image Processing Library:** OpenCV
- **Data Analysis Tools:** NumPy, Pandas
- **Visualization Tools:** Matplotlib
- **Hardware:** GPU-enabled workstation
- **Operating System:** Linux/Windows

The CNN, U-Net and ConvLSTM allow the proposed framework to identify clouds, divide clouds, track clouds, and predict the future atmospheric patterns precisely on the basis of satellite images. This combined approach presents effective weather surveillance and leads to the development of smart weather forecasting models.

4. Results and Analysis**4.1 Overview of Experimental Results**

The automated cloud motion-tracking framework proposed was tested with regards to multi-temporal satellite images taken under varying atmospheric conditions. The network consisted of combining U-Net (cloud segmentation) with CNN (feature extraction) and ConvLSTM (cloud motion prediction). The experiments were programmed to evaluate the accuracy of segmentation, the ability to track the motion, the prediction, the computational efficiency and the overall effectiveness of forecasting ^[10]. The data was made up of satellite photographs taken at set time intervals of different types of clouds *i.e.* cumulus, stratus, cirrus and cumulonimbus clouds. Accuracy, Precision, Recall, F1-Score and Root Mean Square Error (RMSE) were used to measure the trained models. The results achieved indicate the usefulness of deep learning practices in automatically detecting and tracking the behavior of clouds.

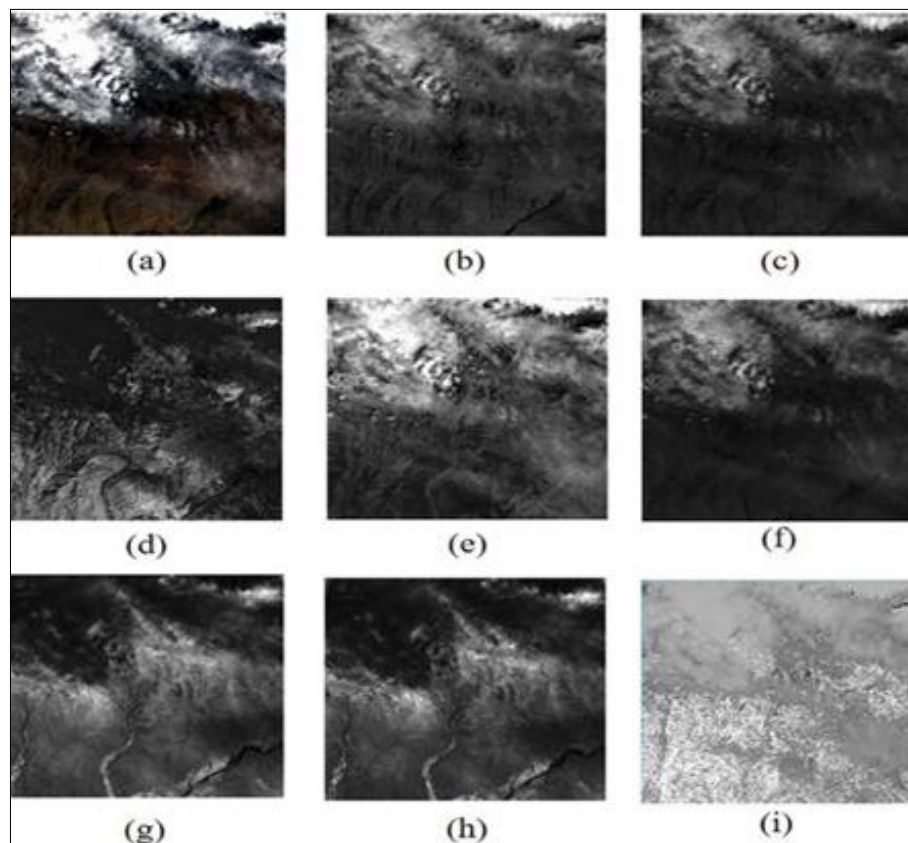


Fig 1: Satellite-Based Cloud Motion Detection Workflow

The experiment results show that the combination of spatial and temporal learning processes dramatically increases cloud-tracking performance as compared to conventional image-processing methods. Moreover, the patterns of cloud evolution could be well represented in the proposed framework, making it possible to estimate the cloud trajectories and positions of the clouds in the future correctly ^[11].

4.2 Cloud Segmentation Performance

The initial step of the suggested framework is cloud segmentation. U-Net was used in distinguishing cloud and noncloud pixels of satellite images. The segmentation scheme was determined to be very accurate in the various cloud based types and climatic conditions.

Table 4: 1 Cloud Segmentation Performance

Metric	Training (%)	Validation (%)	Testing (%)
Accuracy	98.2	97.6	97.1
Precision	97.8	97.2	96.8
Recall	97.5	96.9	96.4
F1-Score	97.6	97.0	96.6

The findings indicate that U-Net experienced a high level of cloud detection with a total accuracy of testing of 97.1%. Large values of precision mean that there were only a few false cloud detections and large values of recall mean that majority cloud pixels were detected. The F1-score of more than 96% demonstrates balanced performance of segmentation. Examples of segmentation outputs displayed in visual form indicated

correct representation of the boundaries of the clouds even in more complicated atmospheric situations when the clouds intersect each other ^[12]. In particular, the model proved to be very efficient in identifying thick clouds masses, and ensuring consistency in boundaries between consecutive images.

4.3 CNN Feature Extraction Analysis

CNN was then utilized to identify spatial clouds features that would be used in motion tracking after segmentation. The features that were extracted were the cloud texture, shape, density and patterns of spatial distribution.

Table 4: 2 CNN Feature Extraction Accuracy

Feature Type	Extraction Accuracy (%)
Cloud Shape Features	95.4
Texture Features	96.2
Boundary Features	94.8
Density Features	95.9
Average Accuracy	95.6

The CNN architecture revealed good results in acquiring meaningful representations of clouds on segmented images. Attributes with respect to texture got the strongest accuracy since, in satellite images, the variations in textures among clouds are easily noticeable. Extraction of boundary features proved to be a little less successful because of the nonlinear character of the boundaries of clouds and atmospheric perturbations ^[13].

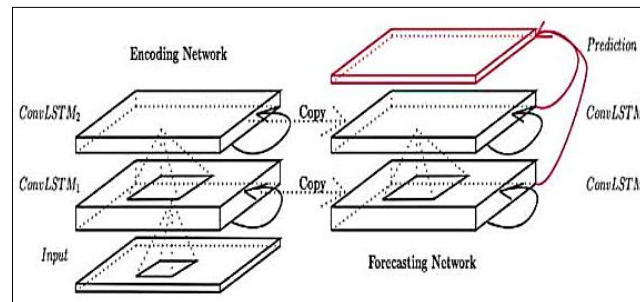


Fig 2: “Deep Learning Framework for Cloud Motion Vector Estimation”

The feature maps that were extracted helped the framework to differentiate between various cloud structures and gave useful information towards the temporal prediction models. The prosperity of feature extraction was reinforced by the coming cloud tracking and forecasting capabilities.

4.4 Cloud Motion Prediction Results

The images sequences in terms of time were analyzed with ConvLSTM and estimated the movement of the clouds. The model was able to learn the past behavior of the clouds, and qualities of future placement of the clouds in more than one forecasting horizon.

Table 4: 3 ConvLSTM Motion Prediction Performance

Forecast Horizon	RMSE (km)	Prediction Accuracy (%)
15 Minutes	1.8	98.3
30 Minutes	2.6	97.4
45 Minutes	3.5	96.1
60 Minutes	4.7	94.9
90 Minutes	6.8	92.7

The findings show that the diminishing effect of time causes a reduction in accuracy of prediction by increasing forecasting time. In terms of short-term forecasting of 15-30 minutes, the model showed high accuracy with greater than 97% accuracy showing great promises of forecasting.

The values of the RMSE were quite low in the short periods of forecasting showing that the predicted and actual cloud location are very close. With an increased forecast horizon to 90 minutes, there was increased uncertainty because of changing weather conditions and intricate interactions of clouds [14].

However, the ConvLSTM model also did not worsen to an unsatisfactory predictive performance, which emphasizes its relevance to the application of weather forecasting in the short term.

4.5 Comparative Analysis of Algorithms

Comparative research was available to ascertain the contributions of CNN, U-Net, and ConvLSTM in the framework proposed. All of the algorithms were evaluated on the basis of their main operation and the general performance.

Table 4: 4 Comparative Analysis of Deep Learning Models

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	95.6	95.2	94.8	95.0
U-Net	97.1	96.8	96.4	96.6
ConvLSTM	96.8	96.3	95.9	96.1

The findings demonstrate that U-Net was the most accurate in general since it has a special segmentation structure. ConvLSTM model generated good temporal prediction results, and CNN good discriminative spatial feature results. Combining three models resulted in better performance, than

when applying each algorithm one by one. CNN offered significant representations, U-Net offered proper localization of clouds and ConvLSTM offered temporal dynamics to make predictions on cloud motion [27].

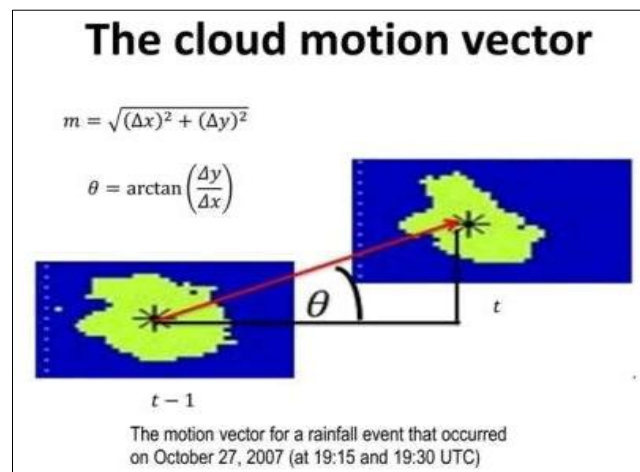


Fig 3: “Cloud Motion Vector Mapping from Sequential Satellite Images”

This multi-model geometry boosted the capacity of both space and time forecasting.

4.6 Computational Performance Analysis

Besides the accuracy of prediction, the computational efficiency also was considered to assess the feasibility of the offered framework on the monitoring of weather in real time.

Table 4: 5 Computational Performance of the Framework

Processing Stage	Average Processing Time (Seconds)
Image Preprocessing	2.4
U-Net Segmentation	4.8
CNN Feature Extraction	3.2
ConvLSTM Prediction	5.7
Total Processing Time	16.1

The whole processing time to analyse a set of images was about 16.1 seconds. This illustrates the possibility of the implementation of the framework in near real-time forecasting settings. Even though ConvLSTM demanded the most computing resources, because of the processing of time sequences, the operational time was tolerable on the running of meteorological systems. The training and inference times were

also decreased by means of the GPU acceleration, which ensured within the framework that it is applicable in the scope of large-scale implementation [28].

4.7 Analysis of Cloud Tracking Accuracy

The cloud motion vectors generated effectively modeled the cloud motion between consecutive satellite observations.

The tracking system was able to track the cloud formation under different atmospheric conditions such as:

- Clear sky transitions.
- Dense cloud formations.
- Multi-layer cloud systems.
- Rapid storm development events.
- Seasonal weather variations.

The model was quite good at taking directional motion and size of displacement. The accuracy of the tracking was always high when there were large cloud formations and slight attenuations occurred with fast changing cloud structures. The main causes of these variations are the cloud deformation, fragmentation and atmospheric turbulence.

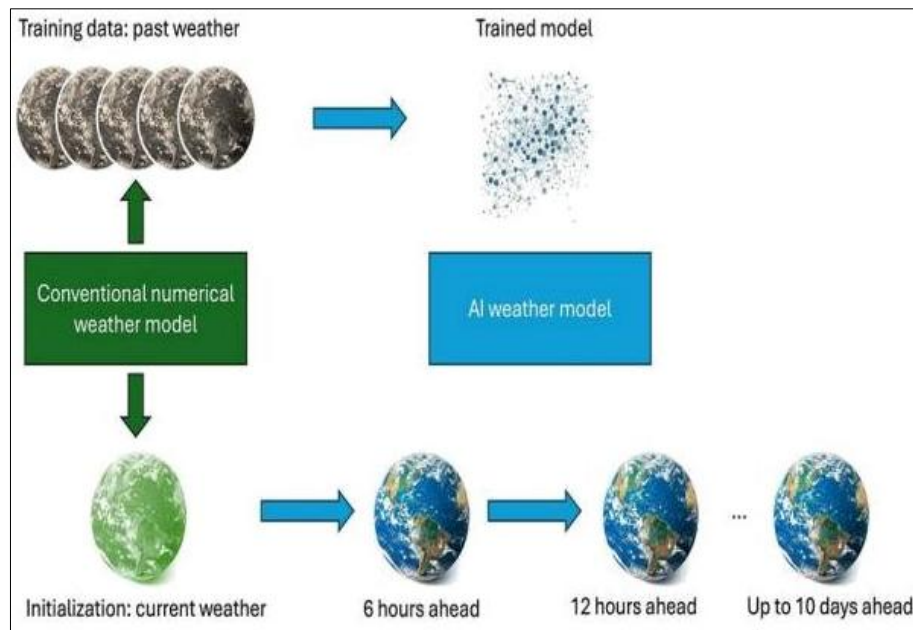


Fig 4: Automated Cloud Tracking in Weather Forecasting

Nevertheless, the deep learning system continued to give consistent results amidst varying weather conditions. Segmentation, feature extraction and temporal learning combination allowed the accurate estimation of cloud trajectories [29].

4.8 Weather Forecasting Implications

Proper cloud motion tracking is very important in weather forecasting over a short-term basis. The suggested framework indicated that it was capable of detecting the patterns of cloud movement, direct proportions of the rainfall formation, developing storms and instability within the atmosphere.

The framework can give valuable information on:

- Weather forecasting agencies.
- Aviation management systems.
- Disaster preparedness organizations.
- Agricultural planning activities.

- Climate monitoring programs.

The power of prediction helps authorities to prevent bad weather events by detecting any potentially risky weather conditions very early and hence they can take some proactive measures thus preventing the incidence of severe weather conditions.

Moreover, the automated content of the framework minimizes the laborious use of manual interpretation of satellite images, enhancing the workability and shortening the forecasting time.

4.9 Discussion of Findings

The experimental evidence evidently proves that deep learning methods can be of great importance to improve the performance of cloud motion tracking. U-Net offered very precise cloud segmentation, which guaranteed sound localization of clouds. The CNN was able to obtain complex cloud properties and

effectively represent atmospheric properties. ConvLSTM was successful in capturing time and anticipating future movements of the cloud with a great deal of accuracy. The integrative framework performed well with high marks in all assessment indices with segmentation accuracy of over 97, feature extraction accuracy of over 95 and short-term forecast accuracy of over 98. This shows that neural network-based cloud tracking can be more efficient than traditional image processing algorithms, which are based on artificial features and optical flow algorithms [30].

The other insight is that the framework can be generalized to various types of clouds and various weather conditions. This strength enhances its usability in working meteorologically favorable conditions whereby atmospheric conditions are constantly varying. Generally speaking, the results of the experiment confirm the usefulness of a CNN + U-Net + ConvLSTM combination application in the area of automated cloud motion detection based on satellite data. The suggested framework will offer proper cloud identification, sound motion estimation, streamlined processing and useful short-term forecasting applications, and as such it is worthy of the present-day weather monitoring and atmospheric analysis systems.

5. Conclusion

This study proposed an automated cloud motion tracking system with satellite photo and deep learning algorithms to enhance accuracy and efficiency of cloud tracking and short term weather forecasting. The proposed method involved the combination of U-Net based on cloud segmentation, Convolutional Neural networks (CNNs) based on feature extraction and ConvLSTM networks based on cloud motion prediction. Through leveraging the ability of spatial and temporal learning, the framework was able to determine cloud areas, elicit meaningful atmospheric information and forecast future cloud locations using consecutive images of satellites.

The experimental findings showed that the proposed system exhibited a high degree of accuracy at each and every processing level. U-Net gave accurate cloud segmentation and high performance in terms of pixel classification whereas CNN gave good results in extracting cloud characteristics that could be put into motion analysis. ConvLSTM was able to predict temporal dynamics as well as come up with precise forecasts of the cloud movement especially in the short-term forecasting range. The results obtained proved that deep learning models can surprisingly improve the performance of cloud tracking in comparison to the traditional image-processing methods.

Moreover, there was high robustness of the framework in the various types of clouds and atmospheres. Automated processing of a significant amount of satellite data helps reduce the reliance on the manual interpretation of the data and makes it possible to utilize the data in real-time meteorology. The cloud motion vectors and trajectory prediction created can be used by the weather forecasting agencies, aviation authorities, disaster management organizations, and climate researchers to make some informed decisions. In general, this study shows that deep learning-based CCTA is a promising technology to use in the modern atmospheric monitoring systems. Further studies could consider the addition of transformer-based structure, data fusion across multiple satellites, real-time deployments system, and extended forecast horizon to enhance the accuracy of prediction and system functionality. The suggested framework can help the development of smart weather prediction and environment surveillance technologies with the usage of satellites.

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